1997-12

A causal based inventory forecasting model for an electronics capital equipment manufacturer

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THESIS

A CAUSAL BASED INVENTORY FORECASTING MODEL FOR AN ELECTRONICS CAPITAL EQUIPMENT MANUFACTURER

By

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December, 1997

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REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	December 1997	Master's Thesis

4. TITLE AND SUBTITLE
A CAUSAL BASED INVENTORY FORECASTING MODEL FOR AN ELECTRONICS CAPITAL EQUIPMENT MANUFACTURER

5. FUNDING NUMBERS

6. AUTHOR(S)
Hicks, John E.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES
The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

With declining budgets for making inventory decisions throughout the business sector, the Navy, and the Department of Defense, the need for accurate inventory demand forecasting is becoming an increasingly important issue. The need for accurate forecasts and adequate inventory models is integral to cost savings, attaining customer service levels, and to the climate of both for-profit and public sector organizations. This thesis develops a forecasting model that attempts to predict future demand by considering several *causal-factors* that might reflect future demand for items. Our results suggest that the model is no better than the current demand-based model, either because our factors did not contain sufficient predictive power, or perhaps because no such factors exist.

14. SUBJECT TERMS
Inventory, Forecasting, Causal

15. NUMBER OF PAGES
46

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFI- CATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
18. Unclassified	19. Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

Approved for public release; distribution is unlimited

A CAUSAL BASED INVENTORY FORECASTING MODEL FOR AN ELECTRONICS CAPITAL EQUIPMENT MANUFACTURER

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN SYSTEMS MANAGEMENT

from the

NAVAL POSTGRADUATE SCHOOL
December 1997

ABSTRACT

With declining budgets for making inventory decisions throughout the business sector, the Navy, and the Department of Defense, the need for accurate inventory demand forecasting is becoming an increasingly important issue. The need for accurate forecasts and adequate inventory models is integral to cost savings, attaining customer service levels, and to the climate of both for-profit and public sector organizations.

This thesis develops a forecasting model for a high-technology firm that attempts to predict future demand by considering several *causal-factors* that might reflect future demand for items. Our results suggest that the model is no better than the current demand-based model, either because our factors did not contain sufficient predictive power, or perhaps because no such factors exist.

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I. INTRODUCTION

With declining budgets for making inventory decisions throughout much of the business sector, the Navy, and the Department of Defense (DOD), the need for accurate inventory demand forecasting is becoming an increasingly important issue. In order to remain competitive in today's environment, all organizations require efficiency and effectiveness in inventory management. The need for accurate forecasts and adequate inventory models are integral to saving costs and attaining customer service levels for both for-profit and public sector organizations.

Demand-based forecasting is an adequate method in a slow growth industry; however, in a high growth industry, such as the technology sector, a demand-based model requires extensive manipulation by individual forecasters to achieve satisfactory results. The individual forecasters' proficiency, flexibility to make decisions, and knowledge of the product lines are key factors in making an adequate forecast.

In the high-tech arena, a causal based inventory model using multiple regression analysis might more adequately meet the needs of the company. At the same time, the model would reduce the manpower required to manually manipulate the results of the computer-generated model.

A global, multi-billion dollar electronics capital equipment manufacturer provides all the data used in this thesis. They are referred to thoughout the thesis as *the test firm* or simply *the firm*.

This thesis focuses on one electronic capital equipment manufacturer that serves high-technology customers. In a private paper, the test firm has identified the following problem statement: "The data, tools and processes used to develop global spares inventory stocking levels, are not robust enough to provide a level of accuracy to achieve optimal asset performance, while delivering customer expected service levels."[1] The private paper continues with the inadequacies of the demand-based model currently installed. The paper discusses the lack of available mean time between failure (MTBF) data and the lack of adequate data regarding the installed base configuration in the individual customer plants.

The firm's directors are concerned about the return on inventory investment and their efficiency in managing a quarter billion dollar inventory. In 1996, spares revenue accounted for 11 percent of the test firm's total revenue.[2] The directors are interested in any resource saving initiatives that do not detract from the customer service levels currently in place.

A. PROBLEM DESCRIPTION

One might summarize a typical business life cycle as infancy, growth, maturity, and decline. The test firm has experienced tremendous growth during the past decade and is currently in the growth stage of its life cycle. This stage allows for some inefficiency in delivering the firm's products and support to its customers, because high profit margins tend to mask high costs. The firm will eventually reach the peak of its growth and need to become more efficient as it enters the maturity stage.

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[1] Private Paper, Director, Spares Planning and Support, Research Test Firm, August 1997
[2] Private Paper, Director, Spares Operation, Research Test Firm, March 1997

The firm strives to achieve a 95 percent service level to support high technology customers with relatively slow-moving items. The firm has approximately 76,000 line items, but the high movers (1 demand per workday) only account for 1 percent of demand.

(1,5842)

Table 1.1. Monthly Demand - Top 300 Movers

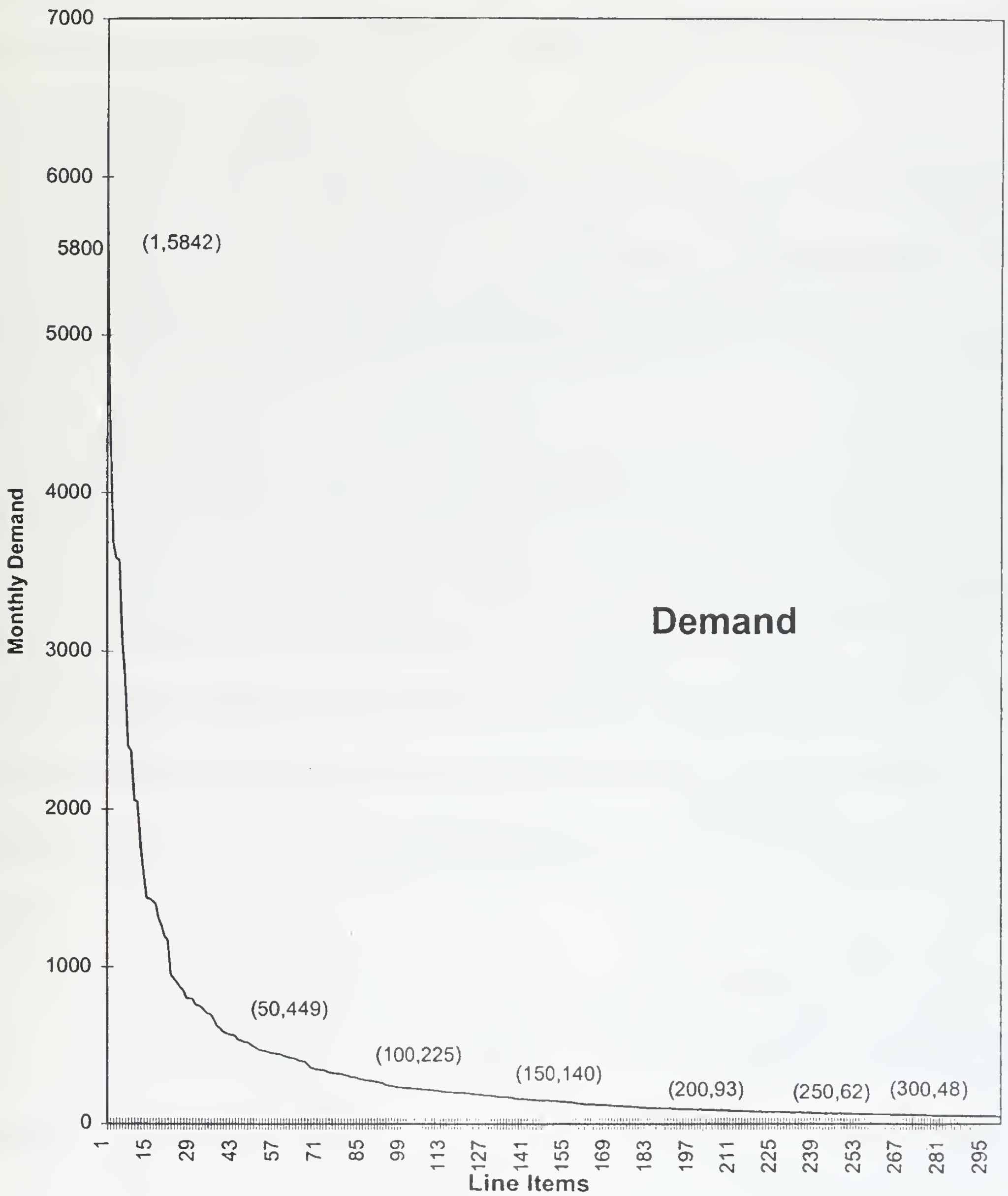


Table 1.1. is a velocity plot of the top 300 high movers for a typical month of demand at the test firm. These top movers consist mainly of filters, gaskets and other low value inventory items. As shown in the table, in a mere 300 line items, less than 0.5 percent of the firm's total line items, demand falls from approximately 5,800 to 48 units demanded in a month.

TABLE 1.2. Monthly Demand Top 301-76,000

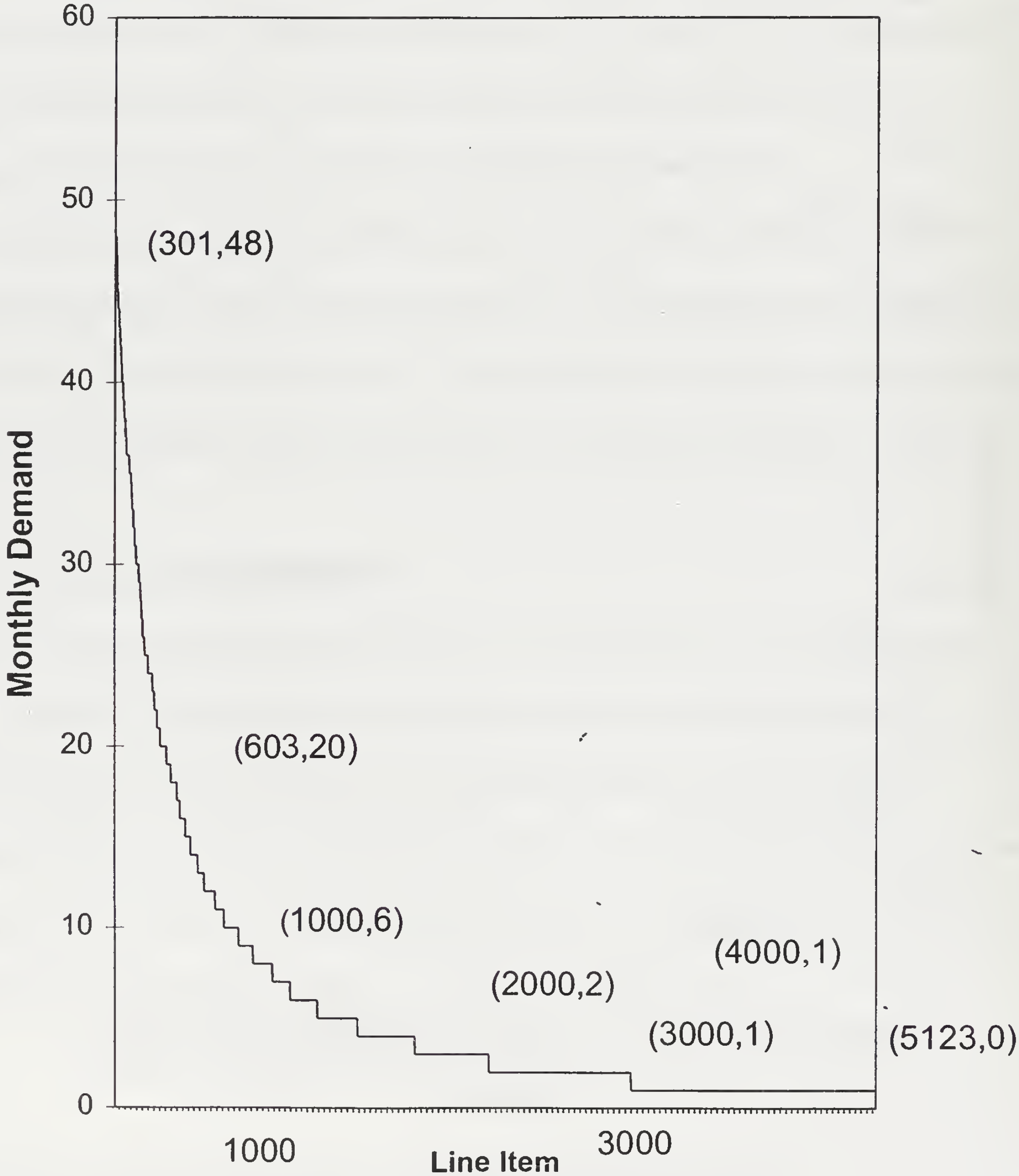


Table 1.2. shows a velocity plot for the remaining 76,000 line items for the month of August 1997. These line items still include certain low valued items, but also include many high valued items. The company may choose to stock only one of these high valued items or even choose to manufacture on demand for the item, in an attempt to reduce holding costs. Table 1.2. shows that by the 700^{th} line item demand is below 20. The table shows that at line item 3,000, demand drops to a single item. The bottom 71,000 line items (over 93 percent of total line items) had no demand in this typical month.

The forecasted items (8 hits in 12 months) account for only 20 percent of the total inventory and only 7 percent of total line items in inventory. The firm currently relies on this demand data and the knowledge of its forecasters to establish an inventory level for specific items.

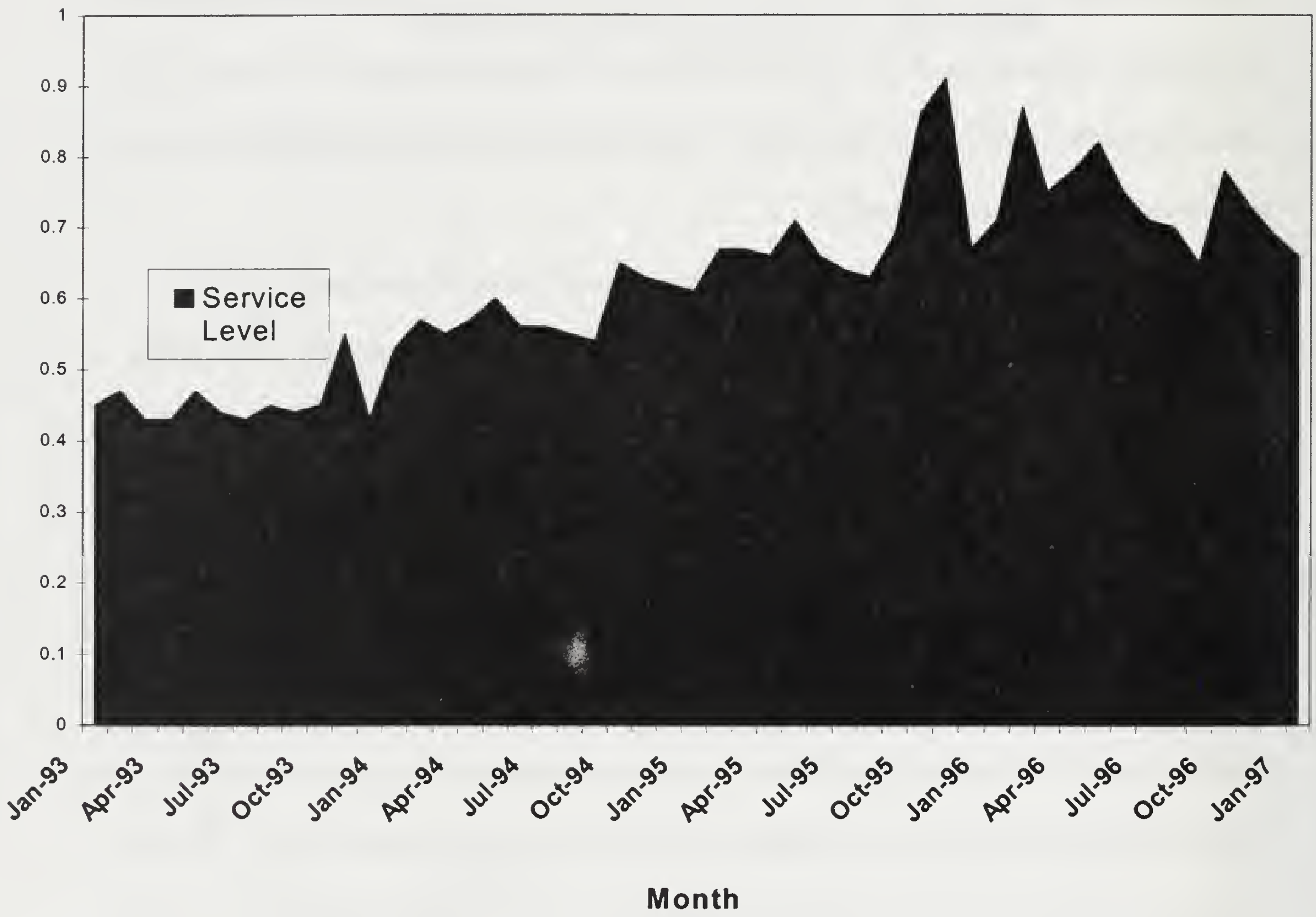
Managers at the firm believe that the demand based forecasting model presently in place does not adequately adjust for new installations, customer workload trends, and aging equipment. The model was installed in October 1995 and relies on a three month moving average to make forecasts. Three months of history is simply not enough data points to make an accurate forecast. The model depends on the opinions of forecasters and their knowledge of the product line, and therefore fails to give adequate forecasts based on the infrequent demand of the "high movers".

The firm currently does not meet a 95 percent service level and routinely maintains only a 60 or 70 percent monthly service level.[3] The service level rarely reaches 80 percent and only once in the last 4 years reached 90 percent.[4] The service level trend is increasing as shown

[3] Private Paper, Director, Spares Operation, Research Test Firm, March 1997
[4] Private Paper, Director, Spares Operation, Research Test Firm, March 1997

in Table 1.3. but still requires tremendous improvement to reach and maintain a 95 percent service level.

Table 1.3. Test Firm's Service Level[5]



Due to a high growth rate over the previous decade, the firm has been able to mask much of its forecasting and inventory problems. Inventory forecasting has not been a central theme in the firm's growth, but it is an element that is now beginning to be reviewed and redeveloped.

[5] Private Paper, Director, Spares Operation, Research Test Firm, March 1997

The firm's total inventory is only $270 million, which is a relatively insignificant amount for the multi-billion dollar company, but holding costs are becoming an increasingly significant issue and total inventory must be reduced 10 percent by the middle of the current fiscal year.[6] If the firm's forecasting methods were more accurate, holding costs might be reduced and service levels may be met.

Further, inventory is becoming an increasingly important topic since many of the stocked items are considered obsolete. Obsolescence occurs in the high-tech sector, not in a matter of years as in many industries, but in a matter of weeks or months.[7] Due mostly to obsolescence, the annual holding cost rate is routinely 50% in the high tech sector.[8]

"The spares demand forecasting process, which drives stocking levels for direct sales and ready to serve inventory, relies on historical data that includes non-conformance and non-recurring demand and is not founded directly on any MTBF element and does not tie directly to the installed base."[9] The firm believes that this is the time to eliminate inefficiencies and is considering either a demand based model known as Distribution Requirements Planning (DRP) or a causal model.

These models will eventually include demand or causal factors, mean time between failures (MTBF), mean time between maintenance (MTBM), operating hours and the installed base in the model's individual analysis. MTBF, MTBM, and operating hours from installed systems is currently unavailable to the test firm but should be included at a later date.

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[6] Private Conversation, Director, Spares Planning and Support, Research Test Firm, August 1997
7 Private Conversation, Forecaster, Research Test Firm, August 1997
[8] Private Conversation, Director, Spares Planning and Support, Research Test Firm, August 1997

[9] Private Paper, Director, Spares Operations, Research Test Firm, March 1997

Information on the installed base is currently only available through an individual analyst's self-developed database.

The installed base is the total of the various configurations of the test firm's systems, installed at customer sites. These systems are owned and maintained by the customers, but over 60 percent of the part support is supplied by the test firm. A private paper described the installed base performance as "the most important manifestation of our commitment to our customers, a catalyst for future business opportunities, and a major business opportunity in itself: profitability and market share."[10]

B. WHY A NEW MODEL IS REQUIRED

The firm believes that a new model is required to meet a 95 percent service level, while reducing the costs associated with inventory and priority shipping.[11] Further, a dozen full-time forecasters are employed in an attempt to reduce the real problem of not having an adequate estimate of future customer demand.

The customer service levels shown in Table 1.3 describes a customer service level goal that the firm cannot currently meet with the present forecasting system. In most instances, the firm is routinely 20 to 35 percent below the target level. The firm currently has a demand-based system in place that requires manual adjustment.[12] The complexity of this problem is increasing due to the high growth of the firm and the increased number of line items stocked in inventory.

Currently, computer-generated forecasts are changed manually by the individual

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[10] Private Paper, Director, Spares Planning and Support, Research Test Firm, August, 1997
[11] Private Conversation, Director, Spares Planning and Support, Research Test Firm, August 1997

[12] Private Conversation, Forecaster, Research Test Firm, August 1997

forecasters, resulting in inefficiencies. These forecasters must rely on their knowledge of the factors affecting their line items, use the results of the demand-based model as a starting point, and manually adjust the computer-generated forecasts up or down to determine the stocking level of the individual line items. The forecasters must account for lead time and dollar value of the line items and must also determine if an item is being phased in or phased out, to avoid shortages or reduce obsolescence.

C. FACTORS NOT ACCOUNTED FOR IN THE DEMAND BASED MODEL

1. Since different forecasting methods are based on historical information, the director must consider how much data is currently on hand, what information it contains, and what it would cost to gather additional data (Wheelwright and Makridakis, 1980). The firm's current demand-based model is lacking much of the rudimentary data required to make adequate forecasts. For example, the firm must also evaluate the recipient costs of not having the information or data available and what this lack of information costs them in increased production, purchasing, expediting and inventory costs. We suggest that the firm either gather or purchase this data from both the firm's manufacturers, and the firm's customers. This will be discussed further in the recommendation section of Chapter IV.

"Particular attention should be paid to whether one is trying to predict the continuance of a historical pattern for a particular item or a turning point for some change in the basic pattern."[13] The demand-based model does not account for these changes to the basic pattern and the forecasters must manually adjust the model. These fluctuations are taken into account to some

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[13] Wheelwright and Makridakis, Forecasting Methods For Management, John Wiley & Sons, Third Edition, 1980, Page 40.

degree by the knowledge of the installations and the customers manufacturing schedule. The individual forecasters review the computer-generated forecasts and add or subtract for the individual line items that they determine require adjusting, when preparing a forecast.

2. The demand-based model does not take into account cyclical business patterns in preparing a forecast. Cyclical business patterns refer to the normal business fluctuations that occur in virtually all industries. The electronics industry reaches a point of under producing, where the industry is selling all the products they have available at a profitable price. The market factors that affect supply and demand are generally considered good for the industry as a whole, during this period. They eventually reach a level due to increased production or new entrants to the industry where they struggle to find a buyer or customer at any profitable price, due to the glut of the item in the marketplace. The test firm is in a cyclical business, yet the current demand-based forecasting model does not account for these patterns. These cycles are different lengths in different industries and are affected by the local, state, national and global economies, but inventory stock levels must be adequately adjusted to alleviate shortages and excess inventories.

3. The current model does not take into account seasonal issues such as Christmas and New Year's plant shut downs. It relies on the individual forecasters to manually adjust these figures. A causal model could not automatically adjust for the fluctuations until MTBM was included as a causal factor and the typical scheduled holiday maintenance was account for.

4. Regional and national differences are not accounted for in the demand-forecasting model. Certain customers who desire a high degree of safety stock may order twice the required amount to augment their individual safety stock. Other companies may choose to maintain virtually no safety stock and rely on expedited shipments for replacement parts. Globally, the

current trend in Asia is to order two parts each time a single part fails, thus showing a higher demand pattern. Additionally, in regional parts of the United States many customers choose to rely on airborne carriers, such as FedEx, to expedite parts that they choose not to stock at the regional depot or local stocking point. This forces the forecasters to be reactive vice proactive. We address the differences between regional depots and local stocking points later in this section.

The model does not separate initial or new installation demand from normal demand. This does not adequately allow either the current model or the individual forecaster in many instances to adequately forecast future demand patterns, because the figure is elevated by the new installation amount. This increases the holding costs for the inventory that is carried based on the inaccuracy of the previous period or period's demand. The additional inventory could very likely not be required because the individual parts may have high reliability rates.

D. INSTALLED BASE SHORTCOMINGS

The company currently does not have complete information of its installed base, nor does it have the ability to determine which parts are being ordered for periodic maintenance, ready spares or actual failure. In not possessing this key information the forecasters are faced with demand patterns that are skewed, which cause difficulties for the demand-based forecasting model and individual forecasters. For example, when one line item fails, the customer orders two parts, one for the failure and one for the ready spare. This would indicate a demand of two. If this part fails again, it might not be ordered at all, or at most one part would be ordered to replace the ready spare. The original two creates a higher stocking level and the second failure

may or may not be reported. If it is not reported a lower than required stocking level might develop.

Consider another example: A customer orders 12 each for periodic maintenance that is conducted every four years. The forecaster increases the forecast, believing this is a normal demand pattern, and the inventory stocking level is increased. However this item may not be required for another four years and may even become obsolete in that time period.

E. EMERGENT ISSUES

The firm currently maintains 55 stocking locations, of which 25 are considered Depots. The stocking locations generally maintain fewer parts than the depots and are designed to support a single customer. Depots are designed to support more than one customer; however, certain depots currently only support an individual customer at a single location. These single customer depots were initially setup with plans to gain additional customers in the geographic area.

The firm maintains computerized stock records on approximately 76,000 line items, but only stocks approximately 28,000 of these. Demand is forecasted for 2,000 of these stocked line items. The firm employs 12 full-time forecasters to validate the computer driven forecasts for these items.

Despite this effort, more than 20 percent of current orders are emergencies a condition in which the right part is not in the right geographic location and must be priority shipped to the customer. Routinely, these parts must be manufactured or purchased at an increased cost to the firm. In the electronics industry, emergencies are reacted to in a critical manner, in much the

same way the Navy reacts to Casualty Reporting (CASREP). Operational issues are deemed critical and expenses are deemed secondary in filling the urgent requirement.

F. DISTRIBUTION REQUIREMENTS PLANNING (DRP) FORECASTING MODEL: THE FUTURE

The firm is in the initial stages of a transition to DRP and is expecting to have DRP online during the 1998 calendar year. DRP should be an improvement over the current system, because it uses a material class ranking system to enable forecasters to key in on the most critical items. Table 1.1 shows how the material class is developed.

The current system must draw on forecaster queries to develop a patterned approach to determine which line items should be manually forecasted. The queries determine which items are most critical and should be worked in descending order. DRP should be able to establish quickly which are the most critical to review by simply keying in on the highest material class and then working methodically through the various classes. An example is an "A3" which has a high value and high demand will be forecasted first under this methodology, whereas a "C0" would be forecasted last. The other items are worked in descending order based on their material class. An example of this order is A3, A2, B3, B2, A1, C3, C2, B1, C1, A0, B0, and C0.

Table 1.4. Development of the Material Class

Demand

Value

	HIGH = 3	MED = 2	LOW = 1	NO = 0
High = A	A3	A2	A1	A0
Med = B	B3	B2	B1	B0
Low = C	C3	C2	C1	C0

DRP relies on moving and weighted averages, single and double smoothing, and linear regression, which are all based on previous demand patterns. DRP uses a 12-month period of demand vice the current system's three-month limitation. The model clearly separates repair from new installations. This change should provide for a more constant demand pattern and allow for a more accurate forecast.

The system provides more flexibility to receive input from other systems, but at this time, none are currently developed. The system will eventually receive MTBF and MTBM input. It will also have data input either by a system or manually for the installed base populations and various configurations. If these inputs were used they would allow for more accurate forecasts.

"As the system is currently planned, it may prove to be reliable but will probably still entail many man-hours, days and years of manual forecasting; until DRP becomes a more integrated method in the total logistics pipeline instead of a stand-alone system."[14] As DRP

becomes more integrated it should provide a much more adequate forecast and may eventually evolve to a level where manual inputs or manual changes to its computer-generated forecasts are unnecessary.

G. RESEARCH OBJECTIVES

The objectives of this thesis are to identify potential inventory stocking policy efficiencies through the development of a causal based model and to identify potential advances that can be implemented. We address the research question: Will a causal based model Provide better forecasts than the existing demand-based forecasting inventory model currently in use?

We analyze the firm's demand, specifically as it relates to inventory decisions, and examine the operational or potentially causative factors that may affect repair parts and consumable demand. We use regression analysis to determine the relationship between those factors. A causal regression model is developed to predict future demand and to establish current inventory stocking policies. The results of the analysis will determine if the causative model is a better predictor of demand than the demand-based models.

H. PREVIEW

Chapter II identifies the causal factors and develops a causal based model. Chapter III analyzes the individual regression model and validates its accuracy. A multiple regression model will be developed based on the results of the individual regressions. Chapter IV provides conclusions and makes recommendations based on the previous chapters.

14Private Conversation, Director, Spares Planning and Support, Research Test Firm, August 1997

II. METHODOLOGY

A. CAUSAL BASED MODELING

Causal based models determine the value of the relationship between the independent variable or variables and the dependent variable. The most common way of determining this hypothetical relationship is with the use of regression analysis.

1. Simple Regression

In the use of simple regression, the starting point is the assumption that a basic relationship exists between two variables and can be represented by some functional form. Mathematically the relationship can be written as:

$$Y = f(X)$$

which simply states that the value of Y is a function of the value of X. Simple regression is a straight-line method and the mathematical function is written as:

$$Y = a + bX$$

where a is the point at which the line intersects the Y-axis. This also implies the use of the error term u (Wheelwright and Makridakis, 1980). "Simple regression uses the least squares method to find the equation for a straight line which most closely approximates the historical observations."[15]

2. Multiple Regression

Multiple regression is generally more accurate than simple regression because it can handle more than one independent variable. There is a limit to the number of

15 Wheelwright and Makridakis, Forecasting Methods For Management, 1980, Page 120

variables that can be used, because of the added complexity and higher costs (Wheelwright and Makridakis, 1980). The costs of accumulating or purchasing data to increase the number of variables, at some point becomes counterproductive. However, the "noise" or residuals must be balanced when determining the number of variables. The error term *u* which denotes the variations not explained by the model, should be reduced to as small a value as possible, which is done by adding variables (Wheelwright and Makridakis, 1980). "Thus we have to try to introduce the smallest number of variables (the principle of parsimony) and at the same time achieve a range of values for *u* as small as possible."[16] The multiple regression equation is written as follows:

$$Y_c = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n$$

Multiple regression also implies the error term *u* (Wheelwright and Makridakis, 1980). We will use both simple and multiple regression to develop the causal based models.

B. DETERMINATION OF CAUSAL FACTORS

As discussed above, causal models are based on the value of the relationship between the independent variables and the dependent variable. Independent variables are selected due to their hypothesized relationship to the dependent variable and their availability over the entire range of the proposed study. Data for the independent and dependent variables was collected for the period September 1995 to August 1997. For realizations of the dependent variable, demand data from the test firm was used. From the approximately 76,000 stock records, records that had at least one demand in each of the previous 15 months were selected; providing just over 1,600 data records. Then 25

16 Wheelwright and Makridakis, Forecasting Methods For Management, 1980, Page 120

data records that had demand over each of the months, in the two-year period, were randomly selected to function as the dependent variable. A data record that did not have a 24-month history was replaced by another randomly selected record with 24 months of demand data.

The independent variables were determined by the availability of data and the hypothesized relationship to the dependent variable. Five independent variables were identified: 1) test firm's stock price, 2) leading customer's stock price, 3) installed base, and 4) number of new installations completed during the month, and 5) age of installed base.

C. CAUSAL FACTORS

1. Test Firm's Stock Price

It was suspected that the stock price might be a good indicator of the test firm's general business direction, profitability, and both short and long term commitments. Stock price might be a good criteria to base inventory stock levels on because it functions as an indicator of the company's general business direction, growth projections and earning estimates. As a company grows and earnings increase, the inventory levels required to increase sales or revenues necessarily increase.

In infancy a company's stock price is low and there is little demand for the companies developing product line or lines and therefore little demand for their inventory. Demand for parts for a company in the growth or maturity levels of the business cycle will be high. In the growth stage a company's installed base is being implemented and there is a need for a high amount of parts and subsequent inventory. In

maturity when a company has many systems installed the inventory would have to be high to support those systems.

A business in the decline stage of the business cycle would out of necessity attempt to reduce inventory and especially inventory holding costs in an attempt to remain a viable business entity. Therefore in infancy where the stock price is low and in decline where the stock price trend is downward inventory levels would tend to be low. In growth and maturity the stock price should be trending upward.

2. Leading Customer's Stock Price

As a supplier of high technology, the test firm's leading customer's stock price might be a good indicator to base inventory stock levels on, for the same reasons stated above. This leading customer provides over 15 percent of the firm's total sales and revenue and therefore is an important segment of the firm's business.

This leading customer's industry is also three to six months ahead of the test firm's industry and could function as a good indicator of market trends which will affect inventory demand three to six months into the future. The leading customer's stock price might indicate inventory levels in forecasting done today by the test firm and allow the lead-time to make the necessary adjustments to inventory levels. This would reduce costs and improve the accuracy of demand forecasting.

3. Installed Base

The installed base is an aggregate total of the test firm's units or systems installed at customers' facilities. This is a key indicator because it identifies the parts required for both the initial outfitting and more importantly for the long-term repair and replacement of failed units. The installed base should eventually transform into a real time data link

that will take into account mean time between failure, mean time between maintenance, and usage data at its customer plants.

This real time data is currently unavailable, but would greatly improve the models, whether they are demand-based or causal. The data would more adequately relate the various reasons for demand to the projected forecasts.

Currently, the installed base data is in the initial stages of development. The only version, albeit rough, is available from an analyst who single-handedly developed a list of the installed base, listing the location, model, and date of installation. While there are configuration differences even among the same models, this is currently the most accurate manner in which to identify and use the data of the installed base.

4. Number of New Installations

Number of new installations relates the amount of new installs that are completed each month. These are systems that are installed in the firm's customer sites and then support for by increased inventories at the test firm. The number of new installations does not take into account machines that are being taken off-line due to obsolescence.

The number of new installations simply identifies a potential relationship between the new installations for a given month and the parts that should be carried to support the installation. This might give an indication of a causal relationship to assist in future demand forecasting.

5. Age of Installed Base

Age of installed base attempts to relate the age of the various customers' installed base to the demand for parts based on the increased need for maintenance and repair as the systems age. This hypothesis is based on the theory that the older the installed base

the greater the number of parts required. This may be a key indicator of the short and long term requirement for parts.

The age of the installed base was computed using the data available on the installed base. Then the total number of systems that were installed in each of the months, of the 24 month test period, were added to the existing systems, and the installed base was aged in each incremental period, by one month.

III. ANALYSIS

A. INITIAL TEST RUNS OF THE REGRESSION ANALYSIS

During the initial test run of regression analysis, the least squared method, which is shown in the Appendix, was used to perform several simple regressions. The initial tests showed a low correlation between the independent and dependent variables.

We hypothesized that each independent variable would not have much relevance until they were combined using multiple regression.

The five independent variables might have some effect on stocking decisions, but taken individually an item such as stock price cannot hope to explain all the intricacies that go into forecasting demand. The initial regressions confirmed this hypothesis.

The coefficient of determination (r^2) was reviewed to determine if the independent variables had some correlation with the dependent variable. This was determined with the use of the F-test. The F-test is used to determine if there is significant correlation at the 95 percent confidence level.

1. F-test

The F-observed statistic needs to be greater than the F-critical value to have a relationship among the variables. When the number of observations is greater than 10 it can roughly be said that the value of F must be greater than five to be significant at the 95 percent confidence level (Wheelwright and Makridakis, 1980). In this thesis the number of observations was 24. The individual results are shown later in the chapter, but for each of the simple regressions, the F-observed value was less than five. Therefore, in all of the

simple regressions any relationship between the dependent and independent variable was determined to be the result of chance (Wheelwright and Makridakis, 1980).

2. T-test

The T-test was subsequently run with negative results. The T-test is used to determine the significance of each coefficient. If the sample size is greater than 15 the T-test must have a value greater than two in order to be significant at the 95 percent confidence level. In each of the individual regressions, the T-test observed value was less than two.

Multiple regression analysis was performed using all five independent variables to determine if the independent variables had a relationship with the dependent variable. The F-Test again shows a relationship based on chance. The T-test for each of the independent variables was also less than two and was deemed insignificant. Both the F- and T-tests are shown in Table 3.2.

The coefficient of determination (r^2) was .303 for the test sample of 25 randomly selected data records. In one of the randomly selected records, r^2 was as high as .49 yet in another it was only .08.

B. INDIVIDUAL REGRESSION MODELS

Table 3.1. summarizes the simple regression analysis for demand in relationship to each of the independent variables. The results indicate that the various r^2 values are not significant per the T-stat value of less than two. An F-Observed value of less than five indicates that any perceived relationship between the independent and dependent variables, occurred merely by chance.

Table 3.1. Simple Regression Analysis for Demand versus Independent Variable

	Independent Variable	r^2	t-stat	F-Observed
1.	Test Firm's Stock Price	.05	1.1	1.25
2.	Leading Customer's Stock Price	.083	1.30	2.33
3.	Installed Base	.079	1.12	2.15
4.	New Installations	.063	1.06	1.70
5.	Age of Installed Base	.076	1.14	2.12

The results indicated that the individual independent variables could not explain the dependent variable. The hypothesis stated earlier that the individual independent variables would not be able to explain the dependent variable was understated. The individual regressions failed to identify virtually any relationship between the independent and dependent and the small one that did exist was simply a matter of chance.

Based on these negative results the five hypothesized potential causal factors were first re-evaluated in an attempt to determine what went wrong in the development of the model. The initial proposed causal factor was the test firm's stock price. When reevaluated it was felt that the dramatic increase in the stock price over the 24-month period in the model was one of the most dramatic two-year increases in U.S. history. We felt that the stock price increase had more to do with the individual market pressures on the stock market, such as relatively low interest rates and lack of alternative investment opportunities. Stock price was reevaluated and determined not to be a good indicator of the proper inventory levels that the firm should maintain.

The second independent variable was the leading customer's stock price. This was flawed for the same reasons stated above.

The third hypothesized causal factor was the installed base. This independent variable was flawed due to the fallibility of the database that the installed base is maintained on. The installed base database does not currently show any deletion of systems and simply identifies the additions.

Additionally, with a lack of MTBF, MTBM, and usage data for the installed base, a causal based model is unlikely to forecast demand any better than a demand-based model.

The fourth independent variable was the number of new installations. The number of new installations may have been flawed because while the aggregate number of new installs was available, the reliability data for these new systems was unavailable. Further, no data was available to indicate if these were replacing existing machines or simply initial outfitting. The hypothesized existing machines may have had two or three times the demand requirements that the new installations now have.

The fifth potential causal factor was age of the installed base. This again had the problem of adding additional units as they came online but no method for identifying those systems that were discarded.

Additionally, the factors not accounted for in the demand-based model, discussed in the initial chapter, were reviewed to determine if our causal model did a better job of accounting for them. The first factor of attempting to account for a change in a basic pattern a causal model is well suited to, however a causal based model will not solve for the other three factors any more than demand-based model currently installed. The

second factor, cyclical business patterns, must be accounted for with time-series analysis vice a causal based model. The third factor, seasonal issues is also best solved with a time-series model vice a causal model. The fourth factor discussed regional and national differences and the causal model developed did not account for these differences. Further, there were no independent variables identified that could account for this fourth factor.

C. MULTIPLE REGRESSION MODEL

A multiple regression model using all the hypothesized independent variables was developed to test the initial hypothesis that together the independent variable may have a relationship with the dependent variable.

The sixth and final model uses multiple regression analysis to compare all of the independent variables to demand. Table 3.2. shows a summary of the results of the multiple regression model. The r^2 of .303 predicts that 30.3% of the total variation is explained by the independent variables. However, the results additionally indicate that the r^2 is not significant per the t-stat value of .971, .939, .1.051, .974, and 1.013 for the respective independent variables which are all less than two that is required for significance at this level. The F-Observed of 1.74 indicates that any proposed relationship between the independent and dependent variables, occurs merely by chance.

Table 3.2. Multiple Regression Analysis for Demand versus All Independent Variables

	Independent Variables	r^2	t-stat	F-observed
1.	Test Firm's Stock Price	.303	.971	1.74
2.	Leading Customer's Stock_Price	.303	.939	1.74
3.	Installed Base	.303	1.051	1.74
4.	New Installations	.303	.974	1.74
5.	Age of Installed Base	.303	1.013	1.74

Grouping the independent variables did not improve the results of the individual regressions. While the r^2 value improved, which is expected in multiple regression, the T-test and F-test did not establish a relationship between the independent and dependent variables.

D. CHECKING THE VALIDITY OF THE REGRESSION ASSUMPTIONS

The independent variables both in the simple and the multiple regression models failed to show a relationship between the independent and dependent variables. These negative results do not satisfy the criteria to attempt to accurately forecast for the dependent variable. Further, the individual regressions showed that the independent variables were not highly correlated, not significant, and resulted merely by chance. The simple and multiple regressions do not give an accuracy expected for this causal model; therefore no forecast was made for the future periods.

IV. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS AND RECOMMENDATIONS

This thesis addressed the need for a new forecasting method at an electronics capital equipment manufacturer. The primary research question asked was: Can a causal based model replace the existing demand-based forecasting inventory model currently in use at an electronics capital equipment manufacturer supporting high technology customers?

1. Transition to DRP

Conclusion: A causal based model was developed which yielded negative results. The thesis research concluded that a demand-based model is a better model at this time. The test firm should transition to DRP as soon as possible.

Recommendation: The test firm should implement the DRP demand-based model and continue to develop accurate information on the installed base of its customers. The firm should develop and implement a database that eventually accounts for the MTBF, MTBM and operating hours for their entire product line. DRP can do this with the correct inputs. The firm's customers and manufacturer must be persuaded to share this data with the firm. If necessary, the firm should purchase this information from its largest customers.

DRP should continue to improve the service level, but without the aforementioned inputs a 95 percent service level is probably unattainable.

2. Need for Accurate Forecasts/Lack of "High Movers"

Conclusion: Due to the lack of "high movers" the firm requires an additional level of safety stock to attain the required customer service level.

Recommendation: The infrequency of demand and an absence of "top movers" will continue to plague the forecasting process, until the firm reaches its maturity level. The firm should carry an extra level of safety stock to increase customer service levels during its current growth stage until it can more adequately forecast demand.

3. Develop and Retain Forecasters

Conclusion: The forecasters are currently an integral part of the forecasting system and need to be developed and retained. DRP may ease the burden on them, however until the other factors affecting the forecasting process can be identified and inputted into the DRP model, the model will require manual adjustments.

Recommendation: The firm further needs to continue to develop and retain their forecasters until they are able to develop or install a more capable system. The forecasters are currently the integral part of the link in reducing inventory costs and improving effectiveness. As more data becomes available, the forecasters should become less critical in inventory forecasting.

4. Identify Global Trends

Conclusion: Global trends must be identified and accounted for by either by the DRP model or through manual forecasting.

Recommendation: The firm needs to identify the causal factors that affect their industry such as market trends or the global economy and use this data to more accurately

forecast future demand. Asia, Europe and several individual countries on both continents greatly affect the demand for parts, revenue and system sales. The firm is integrated into the various global markets and economies and is greatly affected by the market trends that affect those economies. To quantify these effects and potential causal factors, the firm should identify several readily available indexes that their directors determine affect demand for their products.

5. Continue to Identify Regional and National Variances in Demand Patterns

Conclusion: Regional and national differences in demand patterns must be accounted for by either DRP or manually. This will allow for a more normalized demand pattern, which will avoid increased inventory holding costs and shortages. Shortages will result in a lower customer service level.

Recommendation: Regional and national variances in the firm's customers demand patterns need to continue to be identified and implemented into the demand-based model. This will help identify actual demand patterns from perceived patterns as discussed earlier in the thesis.

6. Implement Cyclical Business Patterns and Seasonal Fluctuations into DRP

Conclusion: DRP forecasts will become more accurate if the cyclical business and seasonal trends are taken into account.

Recommendation: Cyclical business patterns and seasonal fluctuations are a part of the firm's business. Therefore these factors must be accounted for as part of DRP, whether directly in the demand based model or as an input from another system.

APPENDIX

Summary of Regression Analysis

Summary of Multiple Regression Analysis

Multiple Regression			customer	test firm	installed base	new install	age
Item #	R Squared	Signifance F	t-stat	t-stat	t-stat	t-stat	t-stat
1	0.487171	3.42	1.8	0.05	0.49	1.46	0.58
2	0.432572	2.74	2.81	1.24	2.13	0.74	2.33
3	0.200854	0.91	0.41	0.27	0.63	0.23	0.5
4	0.185292	0.82	0.2	0.98	0.9	1.04	0.86
5	0.373658	2.15	1.57	1.31	1.37	0.85	1.26
6	0.399293	2.4	0.62	2.76	2.24	2.6	2.24
7	0.491013	3.47	0.25	0.45	0.1	1.62	0.01
8	0.189908	0.84	1.9	0.67	0.31	0.11	0.1
9	0.449774	2.94	0.38	0.33	0.29	2.29	0.2
10	0.312168	1.63	0.71	1.61	1.51	1.17	1.43
11	0.083641	0.33	0.84	0.15	0.11	0.6	0.05
12	0.118168	0.48	1.39	0.48	0.06	0.26	0.19
13	0.395464	2.35	1.68	0.51	0.82	0.24	0.86
14	0.401807	2.42	0.24	2.88	2.21	0.71	2.17
15	0.384105	2.25	0.29	0.26	1.23	1.27	1.11
16	0.278754	1.39	0.36	0.02	0.66	1.19	0.56
17	0.428779	2.7	0.1	2.88	3.04	0.27	3.05
18	0.119959	0.49	1.01	0.02	0.12	0.06	0.02
19	0.288972	1.46	0.78	1.49	1.39	2.59	1.35
20	0.185487	0.82	0.53	0.22	0.62	0.03	0.49
21	0.292217	1.49	1.21	1.05	1.52	0.81	1.35
22	0.311489	1.63	1.33	2.1	2.22	0.69	2.08
23	0.141148	0.59	1.42	0.19	0.09	0.11	0.21
24	0.470296	3.2	0.72	1.04	1.1	3.12	1.3
25	0.156426	0.67	0.93	1.31	1.12	0.28	1.02
Totals	0.3031366	1.7436	0.9392	0.9708	1.0512	0.9736	1.0128

Summary of Individual Regression Analysis

	New Installations			Customer's Stock Price			Test Firm's Stock Price		
Item #	R Squared	Signifance F	t stat	R Squared	Signifance F	t-stat	R Squared	Signifance F	t-stat
1	0.282544	8.66	2.94	0.377916	13.37	3.66	0.091679	2.22	1.49
2	0.007152	0.16	0.4	0.067092	1.58	1.26	0.008128	0.18	0.42
3	0.003185	0.07	0.27	0.045852	1.06	1.03	0.001473	0.03	0.18
4	0.019433	0.44	0.66	0.048979	1.13	1.06	0.047738	1.1	1.05
5	0.039654	0.91	0.95	0.269889	8.13	2.85	0.147846	3.82	1.95
6	0.075873	1.81	1.34	0	0	0.04	0.051066	1.18	1.09
7	0.304878	9.65	3.11	0.292208	9.08	3.01	0.019788	0.44	0.67
8	0.005705	0.13	0.36	0.006061	0.13	0.37	0.000755	0.02	0.13
9	0.012676	0.28	0.53	0.23109	6.61	2.57	0.108982	2.69	1.64
10	0.200925	5.53	2.35	0.085658	2.06	1.44	0.01464	0.33	0.57
11	0	0	1.22	0.046057	1.06	2.27	0.031069	0.71	5.36
12	0.008896	0.2	0.44	0.004913	0.11	0.33	0.007121	0.16	0.4
13	0.012152	0.27	0.52	0.079826	1.91	1.38	0.036749	0.84	0.92
14	0.016479	0.37	0.61	0.08835	2.13	1.46	0.235158	6.76	2.6
15	0.066276	1.56	1.25	0.016844	0.38	0.61	0.073414	1.74	1.32
16	0.089392	2.16	1.47	0.023525	0.53	0.73	0.124382	3.13	1.77
17	0.11752	2.93	1.71	0.067002	1.58	1.26	0.009353	0.21	0.46
18	0.010123	0.22	0.47	0.052005	1.21	1.1	0.067364	1.59	1.26
19	0.119853	3	1.73	0.003315	0.07	0.27	0	0	0.01
20	0.003308	0.07	0.27	0.019086	0.43	0.65	0.012428	0.28	0.53
21	0.000966	0.02	0.15	0.011054	0.25	0.5	0.08273	1.98	1.41
22	0.015022	0.34	0.58	0.059072	1.38	1.18	0.041977	0.96	0.98
23	0.025927	0.59	0.77	0.075717	1.8	1.34	0.024179	0.55	0.74
24	0.075411	1.79	1.34	0.063013	1.48	1.22	0.007793	0.17	0.42
25	0.052174	1.21	1.1	0.035549	0.81	0.9	0.002679	0.06	0.24
Totals	0.062621	1.6948	1.06	0.0828029	2.3312	1.3	0.0499396	1.246	1.1

Summary of Individual Regression Analysis - Continued

	Installed Base			Age of Installed Base		
Item	R Squared	Signifance F	t-stat	R Squared	Significance F	t-stat
1	0.29958	9.41	3.07	0.300069	9.43	3.07
2	0.024165	0.55	0.74	0.017239	0.39	0.62
3	0.116605	2.9	1.7	0.099691	2.44	1.56
4	0.044973	1.04	1.02	0.045279	1.04	1.02
5	0.160754	4.21	2.05	0.18241	4.91	2.22
6	0.005253	0.12	0.34	0.002628	0.06	0.24
7	0.371976	13.03	3.61	0.350427	11.87	3.45
8	0.004115	0.09	0.3	0.003211	0.07	0.27
9	0.248175	7.26	2.7	0.245258	7.15	2.67
10	0.057268	1.34	0.01	0.064246	1.51	1.23
11	0.020849	0.47	0.68	0.024273	0.55	0.74
12	0.000112	0	0.05	0	0	0
13	0.123853	3.11	1.76	0.086364	2.08	1.44
14	0.047583	1.1	1.05	0.059626	1.39	1.18
15	0.091186	2.21	1.49	0.060341	1.41	1.19
16	0	0	0.02	0.002592	0.06	0.24
17	0.066934	1.58	1.26	0.078221	1.87	1.37
18	0.01097	0.24	0.49	0.016386	0.37	0.61
19	0.001435	0.03	0.18	0.0012	0.3	0.16
20	0.078131	0.19	1.37	0.05787	1.35	1.16
21	0.006779	0.15	0.39	0.000671	0.01	0.12
22	0.012814	0.29	0.53	0.021974	0.49	0.7
23	0.031862	0.72	0.85	0.033062	0.75	0.87
24	0.13197	3.34	1.83	0.122267	3.06	1.75
25	0.016222	0.36	0.6	0.017838	0.4	0.63
Total	0.0789426	2.1496	1.12	0.0757257	2.1184	1.14

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